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Abstract *In this study, an interval-parameter robust minimax-regret programming method is developed and applied to the planning of energy and environmental systems. Methods of robust programming, interval-parameter programming, and minimax-regret analysis are incorporated within a general optimization framework to enhance the robustness of the optimization effort. The interval-parameter robust minimax-regret programming can deal with uncertainties expressed as discrete intervals, fuzzy sets, and random variables. It can also be used for analyzing multiple scenarios associated with different system costs and risk levels. In its solution process, the fuzzy decision space is delimited into a more robust one through dimensional enlargement of the original fuzzy constraints; moreover, an interval-element cost matrix can be transformed into an interval-element regret matrix, such that the decision makers can identify desired alternatives based on the inexact minimax regret criterion. The developed method has been applied to a case study of energy and environmental systems planning under uncertainty. The results indicate that reasonable solutions have been generated.*

Keywords decision making, energy, environment, fuzzy set, inexact analysis, minimax regret, robust programming, uncertainty

1. Introduction

Environmental problems associated with social and economic development have been growing concerns faced by many regional, national, and international authorities. Environmental pollution cannot only pose a variety of impacts on public health, but also hinder sustainable regional development. There are many sources of pollutant emissions in a regional system. Among them, energy sector is a major contributor since many countries and regions continue to have heavy reliance on nonrenewable energy resources such as coal, oil, and natural gas. Many conflict-laden issues such as the growing

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population, the boosting economic development, the increasing energy demand, the deteriorating environmental quality, and the shrinking resource availability have called for more effective planning of energy and environmental systems. Moreover, uncertainties exist in a number of energy and environmental systems, leading to further complexities in generating sound plans for satisfying various energy and environmental objectives. Thus, development of effective optimization methodologies that can tackle the above complexities is desired for generating robust bases for supporting decisions of energy and environmental systems planning.

Previously, a number of researchers dealt with uncertainties in energy and environmental systems through stochastic programming (Nordhaus, 1993; Manne et al., 1995; Peck and Teisberg, 1995; Fragnière and Haurie, 1996; Kanudia, 1996; Kanudia and Loulou, 1998; Kanudia and Shukla, 1998; Jaccard et al., 2003; Cofala et al., 2004; Albornoz et al., 2004). Among them, Kanudia and Loulou (1998) introduced a multistage stochastic programming method into the MARKAL model to formulate a long-term plan for mitigating greenhouse gas (GHG) emission in Québec, Canada. MARKAL was a large-scale, technology-oriented, activity analysis model emphasizing energy-related supply and end-use sectors (Fishbone and Abilock, 1981). Albornoz et al. (2004) proposed a two-stage stochastic integer programming model for planning a thermal power system expansion, where uncertainties related to future availability of the power plant were reflected through analyzing a finite group of scenarios. However, the stochastic programming methods were incapable of dealing with uncertainties expressed as possible scenarios with unknown probabilistic distributions. In fact, in many real-world problems, the quality of information that can be acquired is mostly not satisfactory enough to be presented as probabilities.

An attractive technique that could help tackle the above shortcomings was minimax regret (MMR) analysis, which was proposed to determine the hedging alternatives under uncertainty but without known probability for the states of the world (Savage, 1954; Averbakh, 2004). Previously, a few research works based on the MMR analysis were developed for supporting energy and environmental systems planning (Loulou and Kanudia, 1999; Chevé and Congar; 2002; Hoaga et al., 2002; Li and Huang, 2006). For example, Loulou and Kanudia (1999) applied the MMR analysis to determine the hedging GHG mitigation strategy for an energy and environmental management system under uncertainty. More recently, Li and Huang (2006) developed an interval minimax regret programming (IMMRP) method to deal with dual uncertainties of intervals and random variables. However, these methods were incapable of handling ambiguous parameters or problems with fuzzy goals and constraints.

Robust programming (RP), which was based on the concept of fuzzy interval, can reflect both ambiguous coefficients in optimization models and vague information of decision makers' implicit knowledge (Dubois and Prade, 1988; El Ghaoui et al., 1998; Inuiguchi and Sakawa, 1998; Ben-Tal and Nemirovski, 1999, 2002; Liu et al., 2003). The RP can effectively handle uncertainties in both left- and right-hand-side coefficients (in the constraints) as represented by possibilistic distributions. However, the RP methods have difficulties in reflecting random variables in a non-fuzzy decision space, especially when possibilistic and/or probabilistic specifications of the uncertain parameters are not both available.

Therefore, the objective of this study is to develop an interval-parameter robust minimax-regret programming (IRMRP) approach and apply it to the planning of energy and environmental management systems. This method will incorporate techniques of RP, interval-parameter programming (IPP), and MMR analysis within a general optimization framework. It can address uncertainties expressed as interval numbers, fuzzy sets, and random variables. Moreover, it can be used for analyzing all possible scenarios associated with different system costs and risk levels, without any assumptions on their probabilistic distributions. An interval-element cost matrix can be transformed into an interval-element regret matrix and, then, decision makers can identify desired alternatives based on the generated inexact minimax regret (IMMR) criterion.

2. Methodology

RP involves the optimization of a precise objective function within a fuzzy decision space delimited by constraints with fuzzy coefficients and fuzzy capacities (Inuiguchi and Sakawa, 1998). A general RP problem can be defined as follows (Leung, 1988):

$$\text{Min } f = CX \tag{1a}$$

subject to:

$$AX \lesssim B \tag{1b}$$

$$X \geq 0 \tag{1c}$$

where $A \in \{\Re\}^{m\times n}$, $B \in \{\Re\}^{m\times 1}$, $C \in \{R\}^{1\times n}$, $X \in \{R\}^{n\times 1}$, $\Re$ denotes a set of fuzzy parameters and variables, R denotes a set of deterministic numbers, and $\lesssim$ means fuzzy inequality. For a robust linear program, through transforming the m imprecise constraints into 2 km precise inclusive ones that correspond to k a-cut levels, model (1) can be converted into the following deterministic version (Negoita et al., 1976; Leung, 1988; Luhandjula and Gupta, 1996; Li et al., 2006):

$$\text{Min } f = CX \tag{2a}$$

subject to:

$$\sum_{j=1}^{n}(\overline{a}_{ij}^{k} x_j) \leq \overline{b}_i^{k}, i = 1, 2, \cdots, m; k = 1, 2, \cdots, v \tag{2b}$$

$$\sum_{j=1}^{n}(\underline{a}_{ij}^{k} x_j) \geq \underline{b}_i^{k}, i = 1, 2, \cdots, m; k = 1, 2, \cdots, v \tag{2c}$$

$$x_j \geq 0, j = 1, 2, \cdots, n \tag{2d}$$

Obviously, the main limitation of the above RP model lies within its deterministic coefficients for the objective function, which may lead to potential losses of valuable uncertain information. Moreover, the conventional RP methods have difficulties in dealing with uncertainties that are expressed as both discrete intervals and fuzzy sets. The IPP technique is capable of tackling uncertainties (existing in the constraints and objective functions) that can be quantified as discrete intervals (Huang et al., 1992; Li and Huang, 2007; Li et al., 2007; Cai et al., 2007). Therefore, the IPP method can be integrated within the RP framework to generate a hybrid robust interval programming (RIP) model as follows:

$$\text{Min } f^{\pm} = C^{\pm} X^{\pm} \tag{3a}$$

subject to:

$$A_r^{\pm} X^{\pm} \leq B_r^{\pm}, r = 1, 2, \ldots, m_1 \tag{3b}$$

$$\underset{\sim}{A}_t^{\pm} X^{\pm} \leq \underset{\sim}{B}_t^{\pm}, t = m_1, +1, m_1 + 2, \ldots, m \tag{3c}$$

$$X^{\pm} \geq 0 \tag{3d}$$

where $A_r^{\pm} \in \{R^{\pm}\}^{m\times n}$, $B_r^{\pm} \in \{R^{\pm}\}^{m\times 1}$, $\underset{\sim}{A}_t^{\pm} \in \{\Re^{\pm}\}^{m\times n}$, $\underset{\sim}{B}_t^{\pm} \in \{\Re^{\pm}\}^{m\times 1}$; r is the number of non-fuzzy constraints; t is the number of fuzzy constraints; $\Re^{\pm}$ denotes a set of intervals with fuzzy lower and upper bounds; the '$-$' and '$+$' superscripts represent lower and upper bounds of the parameters/variables, respectively.

The MMR analysis technique is useful for handling problems where the worst-case loss (in the objective function) to be minimized while the prior probabilistic function of random variables is unavailable. Let S be a strategy space with $S = \{s_1, s_2, \ldots, s_p\}$, let O be an outcome space with $O = \{o_1, o_2, \ldots, o_q\}$, and U be a real-valued objective function defined as $S \times O$ for a problem of decision analysis under uncertainty. Let $C(s_i, o_j)$ be the cost incurred when alternative a_i is used while outcome s_j occurs. Let r_{ij} be the regret of joint alternative (s_i, o_j), which is defined as the difference between the cost incurred with pair (s_i, o_j) and the least cost under an ideal condition among multiple outcomes (Tummala, 1973). Then, we have:

$$r_{ij} = C(s_i, o_j) - \min_{t\in O} C(s_i, t), \forall s_i \in S, o_j \in O \tag{4}$$

where r_{ij} is always non-negative. To account for uncertainties expressed as both random variables and discrete intervals, techniques of IPP and MMR can be incorporated within a general optimization framework. Consequently, an IMMR can be defined as (Li and Huang, 2006):

$$\text{MMIR} = \min_{S} \max_{O}\{R^{\pm}(s_i, o_j) = r_{ij}^{\pm}\} \tag{5}$$

where $R^{\pm}(s_i, o_j)$ is an inexact regret matrix whose elements are interval numbers $(r_{ij}^{\pm})$. An inexact regret level can reflect not only the difference between the system cost of an examined alternative and the least cost of the best strategy, but also the difference between the lower and upper bounds of each objective function value. Then, through incorporating the IMMR analysis technique within the RIP framework, an IRMRP model can be formulated as follows:

$$\underset{s\in S}{\text{Min}}\{\max_{o\in O} R^{\pm}(s_i, o_j)\} \tag{6a}$$

subject to:

$$A_r^{\pm} X^{\pm so} \leq B_r^{\pm o}, r \in M; s \in S; o \in O \tag{6b}$$

$$\underset{\sim}{A}_t^{\pm} X^{\pm so} \leq \underset{\sim}{B}_t^{\pm}, t \in M, t \neq r; s \in S; o \in O \tag{6c}$$

$$X^{\pm so} \geq 0, s \in S; o \in O \tag{6d}$$

where $B_r^{\pm o}$ are interval-random variables that may take q arbitrary intervals ($b_r^{\pm o_1}$, $b_r^{\pm o_2}, \ldots, b_r^{\pm o_q}$). The objective is to minimize the worst-case regret value under uncertainty. Assume that there is no intersection between the two fuzzy bounds of each $\underset{\sim}{B}_t^{\pm}$. The IRMRP model can be solved through a two-step method. When the system objective is to be minimized, a set of submodels (i.e., $p \times q$ deterministic problems) corresponding to f^- can be firstly formulated and solved; then, the other set of submodels corresponding to f^+ can be formulated based on the solutions for the first set of submodels. Interval solutions for the IRMRP model can then be obtained through integration of the solutions from the two sets of submodels. In detail, for each $b_r^{\pm o}$, the first submodel can be formulated as follows:

$$\text{Min } f_{so}^- = \sum_{j=1}^{j_1} c_j^- x_j^{-so} + \sum_{j=j_1+1}^{n} c_j^- x_j^{+so} \tag{7a}$$

subject to:

$$\sum_{j=1}^{j_1} |a_{rj}|^+ \operatorname{Sign}(a_{rj}^+) x_j^{-so} + \sum_{j=j_1+1}^{n} |a_{rj}|^- \operatorname{Sign}(a_{rj}^-) x_j^{+so} \le b_r^{+o},$$

$$r = 1, 2, \ldots, m_1; s \in S; o \in O \tag{7b}$$

$$\sum_{j=1}^{j_1} \overline{\{|a_{tj}|^+ \operatorname{Sign}(a_{tj}^+)\}}^k x_j^{-so} + \sum_{j=j_1+1}^{n} \overline{\{|a_{tj}|^- \operatorname{Sign}(a_{tj}^-)\}}^k x_j^{+so} \le \overline{b_t^+}^k,$$

$$t = m_1 + 1, m_1 + 2, \ldots, m; k = 1, 2, \cdots, v; s \in S; o \in O \tag{7c}$$

$$\sum_{j=1}^{j_1} \underline{\{|a_{tj}|^+ \operatorname{Sign}(a_{tj}^+)\}}^k x_j^{-so} + \sum_{j=j_1+1}^{n} \underline{\{|a_{tj}|^- \operatorname{Sign}(a_{tj}^-)\}}^k x_j^{+so} \ge \underline{b_t^+}^k,$$

$$t = m_1 + 1, m_1 + 2, \ldots, m; k = 1, 2, \cdots, v; s \in S; o \in O \tag{7d}$$

$$x_j^{-so} \ge 0, j = 1, 2, \cdots, j_1; s \in S; o \in O \tag{7e}$$

$$x_j^{+so} \ge 0, j = j_1 + 1, j_1 + 2, \cdots, n; s \in S; o \in O \tag{7f}$$

where $x_j^{\pm so} (j = 1, 2, \ldots, j_1)$ are interval variables with positive coefficients in the objective function; $x_j^{\pm so} (j = j_1 + 1, j_1 + 2, \ldots, n)$ are interval variables with negative coefficients. Through solving the above $p \times q$ submodels (under different combinations of strategies and outcomes), a set of lower-bound objective-function values can be generated. Thus, a matrix of lower-bound system costs under all scenarios can be obtained as follows:

$$F_{so}^- = \begin{bmatrix} f_{s_1 o_1}^- & f_{s_1 o_2}^- & \cdots & f_{s_1 o_q}^- \\ f_{s_2 o_1}^- & f_{s_2 o_2}^- & \cdots & f_{s_2 o_q}^- \\ \vdots & & & \\ f_{s_p o_1}^- & f_{s_p o_2}^- & \cdots & f_{s_p o_q}^- \end{bmatrix} \tag{8}$$

To generate upper-bound elements for the system-cost matrix, the submodel corresponding to f^+ can be formulated as follows:

$$\text{Min } f_{so}^{+} = \sum_{j=1}^{j_1} c_j^{+} x_j^{+so} + \sum_{j=j_1+1}^{n} c_j^{+} x_j^{-so} \tag{9a}$$

subject to:

$$\sum_{j=1}^{j_1} |a_{rj}|^{-} \operatorname{Sign}(a_{rj}^{-}) x_j^{+so} + \sum_{j=j_1+1}^{n} |a_{rj}|^{+} \operatorname{Sign}(a_{rj}^{+}) x_j^{-so} \le b_r^{-o},$$

$$r = 1, 2, \ldots, m_1; s \in S; o \in O \tag{9b}$$

$$\sum_{j=1}^{j_1} \overline{\{|a_{tj}|^{-} \operatorname{Sign}(a_{tj}^{-})\}^{k}} x_j^{+so} + \sum_{j=j_1+1}^{n} \overline{\{|a_{tj}|^{+} \operatorname{Sign}(a_{tj}^{+})\}^{k}} x_j^{-so} \le \overline{b_t^{-k}},$$

$$t = m_1 + 1, m_1 + 2, \ldots, m; k = 1, 2, \cdots, v; s \in S; o \in O \tag{9c}$$

$$\sum_{j=1}^{j_1} \underline{\{|a_{tj}|^{-} \operatorname{Sign}(a_{tj}^{-})\}^{k}} x_j^{+so} + \sum_{j=j_1+1}^{n} \underline{\{|a_{tj}|^{+} \operatorname{Sign}(a_{tj}^{+})\}^{k}} x_j^{-so} \ge \underline{b_t^{-k}},$$

$$t = m_1 + 1, m_1 + 2, \ldots, m; k = 1, 2, \cdots, v; s \in S; o \in O \tag{9d}$$

$$x_j^{+so} \ge x_{j\text{opt}}^{-so}, j = 1, 2, \cdots, j_1; s \in S; o \in O \tag{9e}$$

$$0 \le x_j^{+so} \le x_{j\text{opt}}^{+so}, j = j_1 + 1, j_1 + 2, \cdots, n; s \in S; o \in O \tag{9f}$$

Through solving the above $p \times q$ submodels, a set of upper-bound objective-function values can be generated. Thus, the matrix of upper-bound system costs under all scenarios can be obtained as follows:

$$F_{so}^{+} = \begin{bmatrix} f_{s_1o_1}^{+} & f_{s_1o_2}^{+} & \cdots & f_{s_1o_q}^{+} \\ f_{s_2o_1}^{+} & f_{s_2o_2}^{+} & \cdots & f_{s_2o_q}^{+} \\ \vdots & & & \\ f_{s_po_1}^{+} & f_{s_po_2}^{+} & \cdots & f_{s_po_q}^{+} \end{bmatrix} \tag{10}$$

Through integrating Eqs. (8) and (10), the matrix of interval system costs can be obtained as:

$$F_{so}^{\pm} = \begin{bmatrix} [f_{s_1o_1}^{-}, f_{s_1o_1}^{+}] & [f_{s_1o_2}^{-}, f_{s_1o_2}^{+}] & \cdots & [f_{s_1o_q}^{-}, f_{s_1o_q}^{+}] \\ [f_{s_2o_1}^{-}, f_{s_2o_1}^{+}] & [f_{s_2o_2}^{-}, f_{s_2o_2}^{+}] & \cdots & [f_{s_2o_q}^{-}, f_{s_2o_q}^{+}] \\ \vdots & & & \\ [f_{s_po_1}^{-}, f_{s_po_1}^{+}] & [f_{s_po_2}^{-}, f_{s_po_2}^{+}] & \cdots & [f_{s_po_q}^{-}, f_{s_po_q}^{+}] \end{bmatrix} \tag{11}$$

where $F_{so}^{\pm} = [F_{so}^{-}, F_{so}^{+}]$, with $s \in S$ and $o \in O$. Then, the matrix of interval system costs can be transformed into a regret matrix with interval elements. Let $f_{s_io_1}^{-}, f_{s_io_2}^{-}, \cdots, f_{s_io_q}^{-}$

be the least lower-bound costs of the best strategy among all possible outcomes of $O = \{o_1, o_2, \ldots, o_q\}$. Thus, we have the following inexact regret matrix:

$$R_{so}^{\pm} = \begin{bmatrix} [f_{s_1 o_1}^{-} - f_{s_i o_1}^{-}, f_{s_1 o_1}^{+} - f_{s_i o_1}^{-}] & [f_{s_1 o_2}^{-} - f_{s_i o_2}^{-}, f_{s_1 o_2}^{+} - f_{s_i o_2}^{-}] & \cdots & [f_{s_1 o_q}^{-} - f_{s_i o_q}^{-}, f_{s_1 o_n}^{+} - f_{s_i o_q}^{-}] \\ [f_{s_2 o_1}^{-} - f_{s_i o_1}^{-}, f_{s_2 o_1}^{+} - f_{s_i o_1}^{-}] & [f_{s_2 o_2}^{-} - f_{s_i o_2}^{-}, f_{s_2 o_2}^{+} - f_{s_i o_2}^{-}] & \cdots & [f_{s_2 o_q}^{-} - f_{s_i o_q}^{-}, f_{s_2 o_q}^{+} - f_{s_i o_q}^{-}] \\ \vdots & & & \\ [f_{s_p o_1}^{-} - f_{s_i o_1}^{-}, f_{s_p o_1}^{+} - f_{s_i o_1}^{-}] & [f_{s_p o_2}^{-} - f_{s_i o_2}^{-}, f_{s_p o_2}^{+} - f_{s_i o_2}^{-}] & \cdots & [f_{s_p o_q}^{-} - f_{s_i o_q}^{-}, f_{s_p o_q}^{+} - f_{s_i o_q}^{-}] \end{bmatrix} \tag{12}$$

where $R_{so}^{\pm} = [R_{so}^{-}, R_{so}^{+}]$ with $s \in S$ and $o \in O$. Then, for each alternative, we can calculate $R_s^{\pm} = \max_o [r_{so}^{\pm}]$ and then identify the desired alternative based on the criterion of $\min_s [R_s^{\pm}]$. Thus, the IMMR can be obtained as follows:

$$\text{IMMR} = \min_s \max_o [r_{ij}^{\pm}], \forall s \in S \text{ and } o \in O \tag{13}$$

The strategy corresponding to a regret level satisfying Eq. (13) is desired. Using the IMMR criterion, a solution with a minimized worst-case loss can be identified before the random variables and their probability distributions are known.

3. Application to Energy and Environmental Systems Planning

3.1. *Overview of the Study System*

For decades, issues of air pollution control have been of substantial concerns since the increasing pollutant concentrations in the ambient environment have caused adverse effects on crops, trees, materials, and human health. The impacts of air pollution are being observed across many regions and socio-economic sectors. Among them, energy sector is a major contributor since consumptions of nonrenewable energy resources (such as coal, oil, and natural gas) can result in emissions of many air pollutants. For example, in North America, over 65% of SO_2 (or more than 13 million tons per year) released to the atmosphere comes from electric utilities that burn coal and natural gas (USEPA, 2004). In Asia, the amount of SO_2 emission from energy sector increased from 12 million tons in 1975 to 27 million tons in 1995 (i.e., with an average annual growth rate of 4.1%) (Streets et al., 2001). Currently, energy demand is experiencing a rapid increase and fossil fuels are still the dominant sources for energy supply (Cofala et al., 2004). In general, coals being mined naturally contain 2.0 to 2.5% of sulfur (Wark et al., 1998). However, even the use of low-sulfur coal (e.g., 0.6%) can hardly satisfy the SO_2 emission standard. Consequently, the increasing demands for fossil fuels are responsible for the increasing SO_2 emissions. This dilemma is linked to both economic development and environmental protection, and has caused extensive attentions at regional, national and international levels.

Since it is economically infeasible or technically impossible to design processes that lead to zero emission of air pollutants, local authorities always seek to control the emissions to levels at which the effects are minimized. The amounts of pollutants released into the atmosphere are related to many factors such as energy input, material throughput, production amount, operating schedule, and device availability (ICF, 1997). Moreover, uncertainties may exist in SO_2 emission levels due to complexities in power

Table 1
SO_2 generation rates and emission allowances at the two sources

	Planning period		
	$k = 1$	$k = 2$	$k = 3$
Level of SO_2 generation (tonne/day):			
(1) Power plant 1			
h = 1 (low)	[110, 130]	[125, 150]	[140, 167]
h = 2 (low-medium)	[131, 159]	[151, 185]	[168, 204]
h = 3 (medium)	[160, 199]	[186, 224]	[205, 249]
h = 4 (high)	[200, 245]	[225, 270]	[250, 295]
(2) Power plant 2			
h = 2 (low)	[62, 80]	[75, 94]	[90, 110]
h = 3 (medium)	[81, 106]	[95, 123]	[111, 140]
h = 4 (high)	[107, 135]	[124, 155]	[141, 175]
SO_2 emission allowance (tonne/day)			
	[[23.5, 35.5] [51.0, 63.0]]	[[23.0, 35.0] [50.0, 62.0]]	[[22.5, 34.5] [49.0, 61.0]]

plant configuration, combustion technology, and fuel composition (Frey et al., 1999). Furthermore, pollution-mitigation processes are related to many factors such as production scale, plant size, and geographical location, as well as boiler size, configuration, and loading pattern (Wark et al., 1998). It is unreasonable that a single desulfurization technology be developed to mitigate SO_2 emission from all types of sources (Wark et al., 1998). Consequently, it is deemed necessary to identify an efficient approach for mitigating SO_2 emissions from multiple pollution sources, in order to comply with the related environmental standards.

Consider an energy system that contains two power plants. The local authority desires to know the technology options with minimized pollution abatement costs and satisfied environmental requirements over a long-term planning horizon (with three 5-year periods). Since the coals used by the two plants have sulfur contents varying from less than 1 to 5% (the sulfur contents of low-sulfur coals can be less than 1%, while those of high-sulfur coals are 2 to 5%), burning coals with different sulfur contents can lead to different emission amounts. From a long-term planning point of view, economic development can result in increased demands for electricity, and thus increased SO_2 emissions generated at each source. Meanwhile, along with economic development and living-standard improvement, more and more environmental requirements will be regulated, which will result in decreases in allowable pollutant-emission amounts.

Table 1 provides several scenarios of SO_2-generation rates and emission allowances at the two power plants. Table 2 shows the efficiencies of different pollution control measures. The efficiency of each measure may fluctuate due to variation in the related

Table 2
SO_2-mitigation efficiency of each measure

Soda ash scrubber (SAS)	Wet limestone scrubber (WLS)	Lime spray dryer (LSD)
[[0.850, 0.870] [0.940, 0.960]]	[[0.780, 0.800] [0.900, 0.920]]	[[0.690, 0.710] [0.840, 0.860]]

Table 3
Economic data of SO_2-emission mitigation

	$k = 1$	$k = 2$	$k = 3$
Cost for mitigating SO_2 emission at power plant 1 ($/tonne):			
Soda ash scrubber (SAS)	[56.9, 72.1]	[62.0, 79.3]	[71.5, 91.4]
Wet limestone scrubber (WLS)	[46.1, 55.2]	[50.1, 60.8]	[58.0, 69.9]
Lime spray dryer (LSD)	[33.2, 40.0]	[36.4, 44.0]	[41.6, 50.5]
Cost for mitigating SO_2 emission at power plant 2 ($/tonne):			
Soda ash scrubber (SAS)	[60.5, 76.7]	[65.9, 84.5]	[75.6, 97.2]
Wet limestone scrubber (WLS)	[44.3, 53.1]	[48.2, 58.5]	[55.8, 67.3]
Lime spray dryer (LSD)	[32.0, 38.4]	[35.0, 42.3]	[40.0, 48.6]
Penalty for excess SO_2 emission ($/tonne)	[96.1, 115.3]	[113.0, 135.6]	[131.2, 157.4]
Waste of resources ($/tonne)	[23.9, 28.7]	[27.6, 33.2]	[32.0, 38.4]

operating conditions such as reagent ratio, temperature, and inlet SO_2 concentration. Table 3 presents the operating costs for mitigating SO_2 emissions to the allowed level, the penalties for excess SO_2 emissions due to the adoption of low-efficiency measures (e.g., lime spray dryer), the wasted resources due to the uses of high-efficiency measures (e.g., wet soda ash scrubber). The penalties could be generated from the uses of high-sulfur coals or low-efficiency mitigation measures; conversely, wasted resources could be due to the uses of low-sulfur fuels or high-efficiency measures. The wet soda ash scrubber (SAS) has a high-acid-removal efficiency; however, it has a relatively high operating cost (due to the high reagent cost). The above cost and technical data were acquired through surveys of many governmental reports and other related literature (Wark et al., 1998; Nevers, 2000; Liu et al., 2003; USEPA, 2005; Li et al., 2006).

For the energy sector, the problem under consideration is how to identify a desired strategy for effectively mitigating SO_2 emission under uncertainty. The IRMRP method is considered to be applicable for tackling these uncertainties. The objective is to minimize the maximum regret value of the cost for SO_2 abatement. Consequently, 108 scenarios will be examined based on 9 mitigation strategies and 12 SO_2-generation outcomes for the two power plants. Each strategy represents one combined option of SO_2-abatement measures for the two power plants, and each outcome refers to an actual realization of SO_2-generation levels at the two sources. Then, a regret matrix with interval elements can be generated from the system-cost matrix based on the procedures as described in Section 2.

3.2. Result and Discussion

Tables 4 and 5 provide the resulting system costs and regret levels under different SO_2-generation rates and mitigation methods. They all present as intervals, demonstrating that the resulting solutions are sensitive to the uncertain inputs. Moreover, the lower-bound system costs and regret levels correspond to scenarios under advantageous conditions, while the upper-bound ones are associated with more demanding conditions. The solutions indicate that variations in the SO_2-generation rates and the control measures may lead to varied system costs. The solutions for system cost under one outcome (i.e., SO_2-generation rates of plants 1 and 2 are both low) will be analyzed below, while those under the other outcomes could be similarly interpreted based on the results presented in Table 4.

When SO_2-generation rates are both low for plants 1 and 2, the cost would be (a) $[101.96, 172.70] $\times 10^6$ if both of the two plants use the SAS technique (i.e., SAS-SAS), (b) $[80.59, 123.95] $\times 10^6$ if plant 1 adopts the SAS while plant 2 uses the wet limestone scrubber (WLS), (c) $[66.48, 106.53] $\times 10^6$ if plant 1 uses the SAS while plant 2 adopts the lime spray dryer (LSD), (d) $[77.26, 117.76] $\times 10^6$ if plant 1 adopts the WLS while plant 2 uses the SAS, (e) $[65.86, 96.03] $\times 10^6$ if both plants 1 and 2 use the WLS technique, (f) $[54.70, 80.26] $\times 10^6$ if plant 1 adopts WLS while plant 2 uses the LSD, (g) $[57.53, 87.62] $\times 10^6$ if plant 1 uses the LSD while plant 2 adopts the SAS, (h) $[52.30, 81.11] $\times 10^6$ if plant 1 adopts the LSD while plant 2 uses the WLS, or (i) $[50.86, 86.90] $\times 10^6$ if both plants 1 and 2 use the LSD techniques. The minimum lower-bound cost would be $50.86 $\times 10^6$ corresponding to the strategy of using the LSD for both of the two plants; the minimum upper-bound cost would be $80.26 $\times 10^6$ when plant 1 adopts the WLS while plant 2 uses the LSD.

Table 5 provides the resulting regret levels under different scenarios. They reflect the difference between the cost incurred under each examined strategy and the least cost under the best one (among all possible outcomes), as well as the difference between the lower and upper bounds of the system cost that correspond to advantageous and demanding conditions. For example, if both of the two plants adopt the SAS technique, the maximum regret level would be $[51.10, 121.84] $\times 10^6$, demonstrating that the largest disparity would occur when the SAS is adopted under the low SO_2-emission level. The solutions under the other conditions could be similarly interpreted based on the results presented in Table 5. Figure 1 presents the maximum regret levels under different strategies for mitigating SO_2 emissions. The minimax lower-bound regret level would be $9.28 $\times 10^6$ when plant 1 adopts the WLS while plant 2 uses the LSD; the minimax upper-bound regret level would be $66.35 $\times 10^6$ when both plants 1 and 2 adopt the WLS technique. Based on the IMMR criterion, therefore, techniques of WLS (for plant 1) and LSD (for plant 2) would be used under advantageous conditions, and the WLS technique for both plants 1 and 2 would be used under demanding conditions.

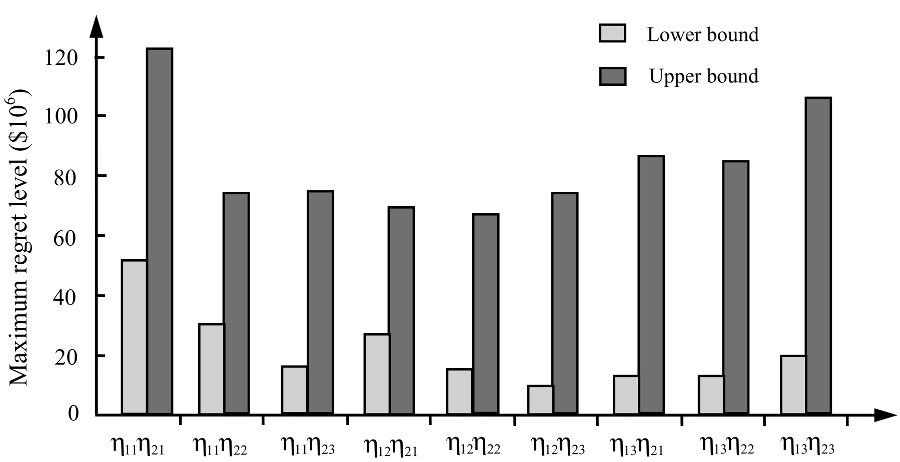


Figure 1. Maximum regret levels under different strategies.

Table 4
Solutions of system costs under different scenarios

Mitigation technique	SO_2-generation rate					
	L-L	L-M	L-H	Lm-L	Lm-M	Lm-H
SAS-SAS	[101.96, 172.70]	[106.30, 180.91]	[112.45, 190.20]	[106.87, 181.53]	[111.21, 189.74]	[117.36, 199.03]
SAS-WLS	[80.59, 123.95]	[82.96, 128.03]	[86.32, 132.64]	[86.79, 135.55]	[89.16, 139.63]	[92.53, 144.24]
SAS-LSD	[66.48, 106.53]	[67.34, 111.94]	[73.72, 127.11]	[73.45, 119.51]	[75.68, 127.81]	[85.14, 145.33]
WLS-SAS	[77.26, 117.76]	[82.62, 128.29]	[90.21, 140.21]	[80.50, 123.05]	[85.86, 133.58]	[93.48, 145.50]
WLS-WLS	[65.86, 96.03]	[68.21, 100.11]	[75.23, 110.54]	[69.08, 101.32]	[74.74, 111.68]	[86.30, 127.84]
WLS-LSD	[54.70, 80.26]	[60.28, 94.36]	[73.03, 116.00]	[63.51, 96.71]	[71.80, 113.87]	[86.74, 137.95]
LSD-SAS	[57.53, 87.62]	[65.38, 101.97]	[76.96, 120.19]	[64.71, 104.78]	[74.51, 121.32]	[88.65, 141.47]
LSD-WLS	[52.30, 81.11]	[59.12, 94.72]	[72.30, 114.32]	[62.32, 101.63]	[71.54, 119.53]	[87.24, 139.71]
LSD-WLS	[50.86, 86.90]	[60.34, 108.01]	[77.84, 131.82]	[63.76, 112.33]	[76.09, 133.40]	[93.59, 157.21]

Mitigation technique	SO_2-generation rate					
	M-L	M-M	M-H	H-L	H-M	H-H
SAS-SAS	[113.48, 192.34]	[117.82, 200.55]	[123.97, 209.84]	[121.59, 204.31]	[125.92, 212.52]	[132.08, 221.81]
SAS-WLS	[95.13, 149.74]	[97.51, 153.82]	[103.96, 162.13]	[105.35, 165.45]	[110.81, 173.23]	[121.29, 179.36]
SAS-LSD	[83.36, 136.10]	[88.94, 148.09]	[101.55, 168.13]	[99.56, 158.45]	[107.71, 172.35]	[122.92, 194.94]
WLS-SAS	[85.46, 129.54]	[93.51, 142.39]	[105.28, 158.78]	[100.84, 145.79]	[111.09, 163.32]	[128.90, 183.21]
WLS-WLS	[79.80, 117.54]	[88.57, 133.39]	[102.48, 153.36]	[99.31, 143.53]	[110.30, 163.98]	[127.72, 187.64]
WLS-LSD	[83.06, 119.42]	[92.97, 140.72]	[110.70, 164.79]	[100.36, 149.09]	[112.85, 170.36]	[130.57, 194.43]
LSD-SAS	[81.15, 133.68]	[92.31, 151.87]	[108.38, 172.46]	[106.82, 167.96]	[118.14, 186.15]	[134.21, 206.74]
LSD-WLS	[81.02, 132.62]	[92.34, 150.54]	[108.41, 170.71]	[106.85, 166.90]	[118.17, 184.82]	[134.24, 204.98]
LSD-WLS	[84.92, 143.32]	[97.25, 164.40]	[114.76, 188.20]	[110.75, 177.60]	[123.08, 198.68]	[140.59, 226.21]

Note. (1) The L-L, L-M, and L-H represent that the SO_2-generation rates of plant 1 are all low, while those of plant 2 are low, medium, and high, respectively.
(2) The Lm-L, Lm-M, and Lm-H represent that the SO_2-generation rates of plant 1 are all low-medium, while those of plant 2 are low, medium, and high, respectively.
(3) The M-L, M-M, and M-H represent that the SO_2-generation rates of plant 1 are all medium, while those of plant 2 are low, medium, and high, respectively.
(4) The H-L, H-M, and H-H represent that the SO_2-generation rate of plant 1 are all high, while those of plant 2 are low, medium, and high, respectively.

Table 5
Regret levels under different scenarios

Mitigation technique	SO_2-generation rate					
	L-L	L-M	L-H	Lm-L	Lm-M	Lm-H
SAS-SAS	[51.10, 121.84]	[47.18, 121.79]	[40.15, 117.90]	[44.55, 119.21]	[39.67, 118.20]	[32.22, 113.89]
SAS-WLS	[29.73, 73.09]	[23.84, 68.91]	[14.02, 60.34]	[24.47, 73.23]	[17.62, 68.09]	[7.39, 59.10]
SAS-LSD	[15.62, 55.67]	[8.22, 52.82]	[1.42, 54.81]	[11.13, 57.19]	[4.14, 56.27]	[0.0, 60.19]
WLS-SAS	[26.40, 66.90]	[23.50, 69.17]	[17.91, 67.91]	[18.18, 60.73]	[14.32, 62.04]	[8.34, 60.36]
WLS-WLS	[15.00, 45.17]	[9.00, 40.99]	[2.93, 38.24]	[6.76, 39.00]	[3.20, 40.14]	[1.16, 42.70]
WLS-LSD	[3.84, 29.40]	[1.16, 35.24]	[0.73, 43.70]	[1.19, 34.39]	[0.26, 42.33]	[1.60, 52.81]
LSD-SAS	[6.67, 36.76]	[6.26, 42.85]	[4.66, 47.89]	[2.39, 42.46]	[2.97, 49.78]	[3.51, 56.26]
LSD-WLS	[1.44, 30.25]	[0.0, 35.60]	[0.0, 42.02]	[0.0, 39.31]	[0.0, 47.99]	[2.10, 54.57]
LSD-WLS	[0.0, 36.04]	[1.22, 48.89]	[5.54, 59.52]	[1.44, 50.01]	[4.55, 61.86]	[8.45, 72.07]

Mitigation technique	SO_2-generation rate					
	M-L	M-M	M-H	H-L	H-M	H-H
SAS-SAS	[33.68, 112.54]	[29.25, 111.98]	[22.42, 108.29]	[22.28, 105.00]	[18.21, 104.81]	[10.79, 100.52]
SAS-WLS	[15.33, 69.94]	[8.94, 65.25]	[2.41, 60.58]	[6.04, 66.14]	[3.10, 65.52]	[0.0, 58.07]
SAS-LSD	[3.56, 56.30]	[0.37, 59.52]	[0.0, 66.58]	[0.25, 59.14]	[0.0, 64.64]	[1.63, 73.65]
WLS-SAS	[5.66, 49.74]	[4.94, 53.82]	[3.73, 57.23]	[1.53, 46.48]	[3.38, 55.61]	[7.61, 61.92]
WLS-WLS	[0.0, 37.74]	[0.0, 44.82]	[0.93, 51.81]	[0.0, 44.22]	[2.59, 56.27]	[6.43, 66.35]
WLS-LSD	[3.26, 39.62]	[4.40, 52.15]	[9.15, 63.24]	[1.05, 49.78]	[5.14, 62.65]	[9.28, 73.14]
LSD-SAS	[1.35, 53.98]	[3.74, 63.30]	[6.83, 70.91]	[7.51, 68.65]	[10.43, 78.44]	[12.92, 85.45]
LSD-WLS	[1.22, 52.82]	[3.77, 61.97]	[6.86, 69.16]	[7.54, 67.65]	[10.46, 77.11]	[12.95, 83.69]
LSD-WLS	[5.12, 63.52]	[8.68, 75.83]	[13.21, 86.65]	[11.44, 78.29]	[15.37, 90.97]	[19.30, 104.92]

Figure 2 presents the relationships between SO_2-generation levels and resulting system costs under two extreme strategies with the lowest and highest mitigation efficiencies. If both of the two plants adopt the SAS, a minimum disparity would exist between anticipated and actual system costs under all SO_2-generation conditions. Under this strategy, however, the wasted resources could become the highest when the actual SO_2-generation rate is low; meanwhile, this strategy would be associated with the highest regret level of $[51.10, 121.84] $\times 10^6$. Although this plan would bear the lowest risk of violating the environmental requirement, it is associated with the highest system cost. In comparison, the maximum disparity for system costs would occur when both of the two plants use the LSD technique. Under this strategy, the lowest system cost may be achieved (i.e., $[50.86, 86.90] $\times 10^6$) under the low SO_2-generation level; however, the highest penalty may have to paid when the SO_2-generation rate is high and, at the same time, the system may encounter the highest risk of violating the environmental requirements. In general, an optimistic policy (with low mitigation efficiency) with a low system cost

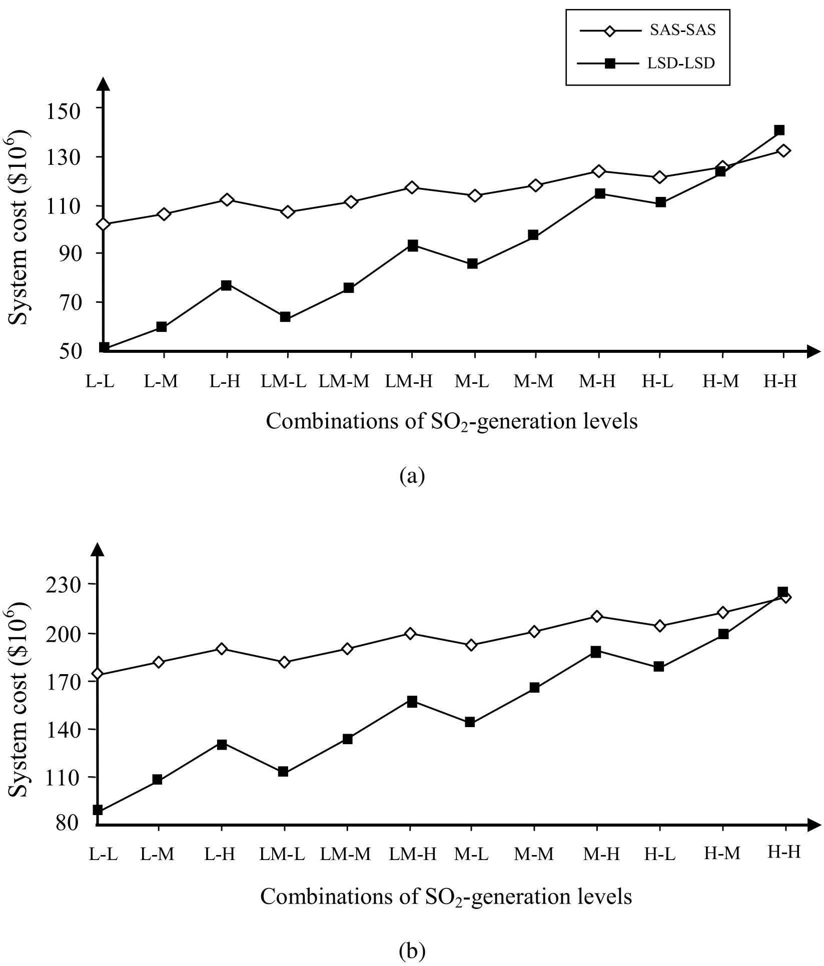
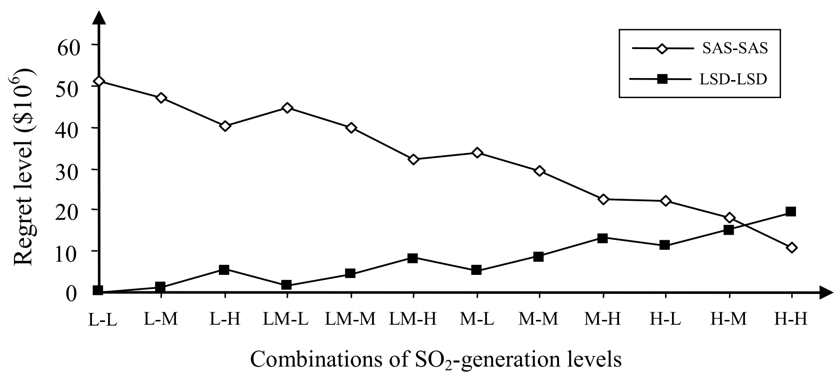


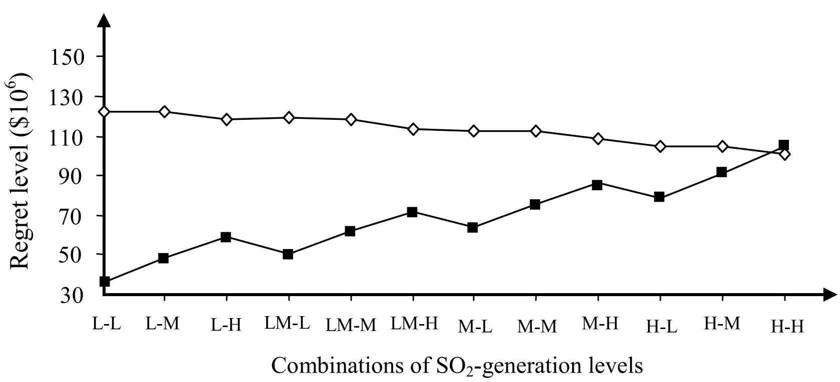
Figure 2. Variations of system costs under the lowest- and highest-efficiency strategies: (a) lower bound and (b) upper bound.

would be subject to a high risk of violating environmental requirements; in comparison, a conservative one (i.e., with high mitigation efficiency) may lead to waste of resources. Therefore, the resulting strategies correspond to various tradeoffs between the economic and environmental considerations.

Figure 3 shows the relationships between the SO_2-generation rates and the corresponding regret levels under two extreme strategies. In most of the outcomes, the regret levels when both of the two plants adopt the SAS technique (named as SAS-SAS combination) would be higher than those when the two plants use the LSD technique (i.e., LSD-LSD combination). Under the SAS-SAS combination (with the highest efficiency), a high regret level implies a serious waste of resources. Thus, planning under a high efficiency strategy (associated with a high system cost) would guarantee that the SO_2-abatement demands and environmental objectives be satisfied, but may result in a high regret level and a serious waste of resources. However, as the plan aims towards a low system cost, a low regret level would be achieved but, at the same time, environmental requirements may not be met. Thus, a tradeoff exists between the regret level and the risk of violating environmental objectives.



(a)



(b)

Figure 3. Regret levels under the lowest- and highest-efficiency strategies: (a) lower bound and (b) upper bound.

Based on the assumed probabilities under the Laplace criterion, the decision makers could calculate the expected system cost and thus identify a desired alternative (Tummala, 1973). In this study, one-twelfth probability was used for each strategy in order to generate the expected system cost. The results indicate that, using the Laplace criterion, under advantageous conditions, the strategy of WLS-LSD method would have a minimum lower-bound expected system cost (i.e., $\$86.71 \times 10^6$); the strategy of WLS-WLS combination would lead to a minimum upper-bound expected system cost (i.e., $\$128.91 \times 10^6$) under demanding conditions. Although the Laplace criterion can also help generate solutions under uncertainty, its assumption in terms of average probabilistic distribution for each random variable is indeed an oversimplification of various stochastic scenarios. In comparison, the IRMRP can deal with multiple uncertainties presented as discrete intervals, fuzzy sets, and random variables; moreover, it adopts a list of scenarios to reflect the uncertainties of random variables without making assumptions on their probabilistic distributions. Moreover, the IRMRP can be used for analyzing all possible scenarios that are associated with different outcomes and strategies. An interval-element regret matrix can be generated based on the interval-element cost matrix obtained from the IRMRP solutions; it can then be used to reflect (a) the difference between the cost under each examined alternative and that under the best one, and (b) the difference between the lower and upper bounds of the objective function value.

4. Conclusions

In this study, an IRMRP method has been developed. Methods of robust programming, interval-parameter programming, and minimax regret analysis are incorporated within a general optimization framework to enhance the robustness of the optimization effort. The IRMRP can deal with uncertainties expressed as discrete intervals, fuzzy sets, and random variables. It can also be used for analyzing multiple scenarios associated with different system costs and risk levels without making assumptions on probabilistic distributions of the random variables. In its solution process, the fuzzy decision space is delimited into a more robust one through dimensional enlargement of the original fuzzy constraints; moreover, an interval-element cost matrix can be transformed into an interval-element regret matrix, such that the decision makers can identify desired alternatives based on the IMMR criterion.

The developed method has been applied to a case study of energy and environmental systems planning under uncertainty. The results indicate that reasonable solutions have been generated. Tradeoffs exist among the system cost, the regret level, and the risk of violating environmental requirements. Although this study is the first attempt for planning an energy and environmental management system through the developed IRMRP approach, the results suggest that this robust programming method is also applicable to many other environmental management problems; it can also be integrated with other optimization methods to handle more complex management problems under uncertainty.

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